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(54) **SYSTEM AND METHOD FOR QUANTITATIVE ANALYSIS OF BOREHOLE IMAGES**

SYSTEM UND VERFAHREN ZUR QUANTITATIVEN ANALYSE VON BOHRLOCHBILDERN

SYSTÈME ET PROCÉDÉ D’ANALYSE QUANTITATIVE D’IMAGES DE PUITS DE FORAGE

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WO-A2-2014/070572

- **BASU T ET AL: "Facies analysis: Integration of core and log data using a neural network as input for reservoir modeling in Betty Field, Malaysia", INTERNET CITATION, 1 August 2004 (2004-08-01), XP001210333, Retrieved from the Internet <URL:http://library.seg.org/doi/pdf/10.1190/1.1786905> [retrieved on 20140630]**

EP 3 871 019 B1

Description

[0001] <DELETED>
[0002] <DELETED>

TECHNICAL FIELD

[0003] The disclosed embodiments relate generally to techniques for quantitative analysis of borehole images obtained from a wellbore through a subsurface volume of interest and, in particular, to a method of estimating net sand in a formation traversed by a wellbore by analysis of borehole images from the wellbore.

BACKGROUND

[0004] Deepwater reservoirs often consist of highly laminated sand-shale sequences, where individual beds are too fine to be fully resolved by standard logs. Note that as is understood in the art, the term sand may refer to sandstone. Without appropriate characterization, thin beds could be under-estimated or neglected, which leads to pessimistic predictions on hydrocarbon pore volume and well deliverability, and reservoir quality is routinely under-predicted. Consequently, laminated reservoirs are considered a common struggle for petrophysical analysis.

[0005] To characterize the thin beds with better accuracy, one could take advantage of high-resolution borehole images, which can detect extremely small formation features (e.g., millimeter scale). In traditional thin-bed analysis, sand counting is usually done by applying a user-specified cutoff on a 1-D high-resolution curve extracted from borehole images. The workflow generally requires meticulous image QC, multiple pre-processing steps and log calibration, and the results are often highly sensitive to the cutoff selection. Moreover, due to the uncalibrated nature of borehole imaging tools, cutoffs selected in one well are not necessarily applicable to other wells, even if they share the same formation systems. This has prevented consistent standards while evaluating multiple wells in one field or asset. Reference may be made to WO 01/31365 A1 which relates to a system and method for enhanced vertical resolution magnetic resonance imaging logs. Reference may be made to WO 2015/127349 A1 which relates to systems, methods, and computer medium to produce efficient, consistent, and high-confidence image-based electrofacies analysis in stratigraphic interpretations across multiple wells. Reference may be made to WO 2014/070572 A2 which relates to rock facies prediction in non-cored wells from cored wells.

[0006] The ability to define the location and quantity of hydrocarbons in the subsurface is crucial to our ability to make the most appropriate choices for purchasing materials, operating safely, and successfully completing projects. Project cost is dependent upon accurate prediction of the position of physical boundaries within the Earth. Decisions include, but are not limited to, budgetary planning, obtaining mineral and lease rights, signing well commitments, permitting rig locations, designing well paths and drilling strategy, preventing subsurface integrity issues by planning proper casing and cementation strategies, and selecting and purchasing appropriate completion and production equipment.

[0007] There exists a need for improved characterization of thin beds in the subsurface to allow improved quantification of hydrocarbons in place in subsurface reservoirs.

SUMMARY

[0008] A method of borehole image analysis according to the present invention is defined in claim 1. Specific embodiments are defined in the dependent claims.

[0009] In another aspect of the present invention, to address the aforementioned problems, some embodiments provide a non-transitory computer readable storage medium storing one or more programs as defined in claim 8. The one or more programs comprise instructions, which when executed by a computer system with one or more processors and memory, cause the computer system to perform any of the methods provided herein.

[0010] In yet another aspect of the present invention, to address the aforementioned problems, some embodiments provide a computer system as defined in claim 7. The computer system includes one or more processors, memory, and one or more programs. The one or more programs are stored in memory and configured to be executed by the one or more processors. The one or more programs include instructions that when executed by the one or more processors cause the computer system to perform any of the methods provided herein as defined in claim 6.

BRIEF DESCRIPTION OF THE DRAWINGS

[0011]

Figure 1 illustrates a flowchart of a method of borehole image analysis, in accordance with some embodiments:
Figure 2 illustrates a step of an embodiment;
Figure 3 illustrates a step of an embodiment;
Figure 4 illustrates a step of an embodiment;
Figure 5 illustrates a step of an embodiment;
Figure 6 illustrates a graphical display produced by an embodiment including a result of an embodiment;
Figure 7 illustrates a graphical display produced by an embodiment including a result of an embodiment;
Figure 8 compares a result of an embodiment with the expected answer; and
Figure 9 is a block diagram illustrating a borehole image analysis system, in accordance with some embodiments.

[0012] Like reference numerals refer to corresponding parts throughout the drawings.

DETAILED DESCRIPTION OF EMBODIMENTS

[0013] Described below are methods, systems, and computer readable storage media that provide a manner of analyzing borehole images. These embodiments are designed to be of particular use for borehole image analysis in areas with thin sand beds.

[0014] Reference will now be made in detail to various embodiments, examples of which are illustrated in the accompanying drawings. In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of the present disclosure and the embodiments described herein. However, embodiments described herein may be practiced without these specific details. In other instances, well-known methods, procedures, components, and mechanical apparatus have not been described in detail so as not to unnecessarily obscure aspects of the embodiments.

[0015] The embodiments described herein for borehole image analysis provide ways to generate a Fraction of Sand (F_{sand}) estimate and net-to-gross (NTG) estimate of sand in a formation using a machine-learning algorithm such as a neural network. Compared to conventional methods for estimating sand in a formation with borehole images, such as applying cut-offs on an extracted resistivity log, the embodiments provided herein take full advantage of borehole images as 2D arrays, which reduces uncertainties caused by image calibration, thin-bed effect, etc.; furthermore, the embodiments herein do not require image flattening, pad equalization or averaging; and make non-linear differentiation between sand and non-sand, which better reflects the complexity of real formations. The predicted F_{sand}, which has a higher resolution than what could be derived from standard well logs like Gamma Ray, can be integrated with other logs for petrophysical and geological analysis. Additionally, the machine-learning algorithm, once trained, can be applied to additional wells in a field more reliably compared with conventional resistivity cut-off methods.

[0016] Figure 1 illustrates a flowchart of an embodiment of a method 100 for estimating F_{sand} from borehole images in order to perform petrophysical analysis and/or estimate hydrocarbons in a formation. The method begins by receiving at least one borehole image at native resolution (usually 0.2 - 1.2 inch with 1 inch = 2.54 cm) which is divided into smaller intervals at operation 10. The divided images are labeled with sand fractions identified from cores at operation 12. This is illustrated in Figure 2. Figure 2 includes a depth column, a borehole image log 21, a White Light (WL) core photo 23, an Ultraviolet (UV) core photo 24, and a track highlighting sand intervals identified from core called a sand flag track 22. In Figure 2, the borehole image log 21 has four intervals selected (21A, 21B, 21C, 21D) and the sand flag track 22 has corresponding intervals (22A, 22B, 22C, 22D) with their sand fractions (0.3, 1.0, 0.5, and 0.0, respectively). The sand flag track 22 may be developed from photos of a core such as the WL and UV photos, physical inspection of a core, or any other method for estimating sand fraction (F_{sand}) for depth intervals. The sand fractions from sand flag track 22 are used to label the selected intervals in the borehole image log 21 at operation 12 of method 100. Although this example has four selected intervals, in some embodiments there may be fewer or more intervals as needed in order to characterize the range of sand fractions in the well. There is an optional data augmentation step (operation 11) as illustrated in Figure 3 which may occur before the labeling. The data augmentation is any method designed to alter the training data in a way that can provide additional samples of training data. For example, the four panels at the top of Figure 3 show a process of random azimuthal shift. Each image is randomly shifted in the horizontal direction, so that the sinusoids that represent the sand layers would appear with different phases. As sinusoidal phase on borehole image is interpreted as orientation of sheet-like geological features (bed boundaries, fractures, deformation bands, etc.), this operation is to teach the network that the predicted sand fraction should be invariant as sand layers are inclined to different orientations. The random azimuth shift should not change the sand count (F_{sand}) but will train the machine-learning algorithm to be insensitive to azimuth. In another embodiment shown in the four panels at the bottom of Figure 3, a depth shift may be applied. This shift is a positive or negative vertical shift. This will affect the sand count dependent on the depth shift. This embodiment teaches the machine-learning algorithm that the location of the sand beds is irrelevant. These examples of data augmentation are not meant to be limiting; any process that can be applied to the training data samples to generate additional likely images is within the scope of this invention such as stretching, rotation, flipping, cropping, and the like.

[0017] The method then moves on to the machine-learning steps. Here, by way of example and not limitation, a neural network may be constructed at operation 13. The neural network may be trained and tested at operation 14, for example using training data like that shown in Figure 4. The training and testing may be done iteratively as shown in Figure 5. In the example of Figure 5, the neural network is trained on 85% of the available labeled borehole image log intervals. The remaining 15% is used to test the accuracy of the predicted F_{sand} after each iteration. This iterative process is performed if the accuracy requirements are not met at decision point 16 of method 100, so the neural network is modified at operation 15 and the training and testing are repeated. In Figure 5, after 3 iterations the accuracy is R=0.53481 and the crossplot of the predicted F_{sand} versus the F_{sand} from core shows a cloud of points with no clear trend. A perfect result would have R=1.0 and a trend exactly matching 1:1 in the crossplot. After 42 iterations, the accuracy has improved to R=0.71818 and after 85 iterations the accuracy has improved to R=0.82461. The determination of whether the result is accurate enough may be done with a user-defined threshold or by allowing the machine-learning algorithm to identify it. Once the accuracy requirements are met, the neural network can be used to make F_{sand} predictions at operation 17. These F_{sand} predictions are shown in Figures 6 and 7 in the vertical tracks labeled 60 and 62, respectively, where the darker line is the predicted F_{sand} from method 100 and the lighter line is a F_{sand} that was estimated by a petrophysicist based on the core. The predicted F_{sand} curves are very close to the F_{sand} from the core. The trained neural network can then be used with borehole images from other wells in the same area or wells that are drilled in areas that are believed to be similar to the one from which the training data was derived.

[0018] Referring again to Figure 1, the predicted F_{sand} can then be used in operation 18 for a number of petrophysical analyses. For example, cumulative sand in a formation or an interval can be calculated by summing up the F_{sand} values foot by foot (1 foot = 30.48 cm) is shown in Figure 8. Hydrocarbon in place can then be calculated through equation HCIP = $A \times h_c \times \phi \times (1 - S_w)/B$, where HCIP is hydrocarbon in place, A is the area of the reservoir, h_c is cumulative sand thickness (net sand thickness), ϕ is the porosity of the net sand, S_w is the water saturation of the net sand, and B is the formation volume factor. This will impact decisions on where to drill, optimal wellpaths, and how to complete wells.

[0019] Figure 9 is a block diagram illustrating a borehole image analysis system 500, in accordance with some embodiments. While certain specific features are illustrated, those skilled in the art will appreciate from the present disclosure that various other features have not been illustrated for the sake of brevity and so as not to obscure more pertinent aspects of the embodiments disclosed herein.

[0020] To that end, the borehole image analysis system 500 includes one or more processing units (CPUs) 502, one or more network interfaces 508 and/or other communications interfaces 503, memory 506, and one or more communication buses 504 for interconnecting these and various other components. The borehole image analysis system 500 also includes a user interface 505 (e.g., a display 505-1 and an input device 505-2). The communication buses 504 may include circuitry (sometimes called a chipset) that interconnects and controls communications between system components. Memory 506 includes high-speed random access memory, such as DRAM, SRAM, DDR RAM or other random access solid state memory devices; and may include non-volatile memory, such as one or more magnetic disk storage devices, optical disk storage devices, flash memory devices, or other non-volatile solid state storage devices. Memory 506 may optionally include one or more storage devices remotely located from the CPUs 502. Memory 506, including the non-volatile and volatile memory devices within memory 506, comprises a non-transitory computer readable storage medium and may store well logs, borehole images, and processed data products.

[0021] In some embodiments, memory 506 or the non-transitory computer readable storage medium of memory 506 stores the following programs, modules and data structures, or a subset thereof including an operating system 516, a network communication module 518, and a borehole image analysis module 520.

[0022] The operating system 516 includes procedures for handling various basic system services and for performing hardware dependent tasks.

[0023] The network communication module 518 facilitates communication with other devices via the communication network interfaces 508 (wired or wireless) and one or more communication networks, such as the Internet, other wide area networks, local area networks, metropolitan area networks, and so on.

[0024] In some embodiments, the borehole image analysis module 520 executes the operations of method 100. borehole image analysis module 520 may include data sub-module 525, which handles the well logs and borehole images 525-1 through 525-N. This data is supplied by data sub-module 525 to other sub-modules.

[0025] Image preparation sub-module 522 contains a set of instructions 522-1 and accepts metadata and parameters 522-2 that will enable it to execute the division and labeling of the borehole images as described in method 100, and optionally the data augmentation. The neural network sub-module 523 contains a set of instructions 523-1 and accepts metadata and parameters 523-2 that will enable it to execute the machine-learning operations of method 100. Although this example labels this module as a neural network, it is within the scope of this invention for any machine-learning algorithm, for example generative adversarial networks (GANs), to be used. The hydrocarbon estimation sub-module 524 contains a set of instructions 524-1 and accepts metadata and parameters 524-2 that will enable it to execute petrophysical analyses such as cumulative sand and hydrocarbon in place for method 100. Although specific operations have been identified for the sub-modules discussed herein, this is not meant to be limiting. Each sub-module may be configured to execute operations identified as being a part of other sub-modules, and may contain other instructions, metadata, and parameters that allow it to execute other operations of use in processing data and generate the graphical image including a F_{sand} prediction. For example, any of the sub-modules may optionally be able to generate a display that would be sent to and shown on the user interface display 505-1. In addition, any of the data or processed data products may be transmitted via the communication interface(s) 503 or the network interface 508 and may be stored in memory 506.

[0026] Method 100 is, optionally, governed by instructions that are stored in computer memory or a non-transitory computer readable storage medium (e.g., memory 506 in Figure 9) and are executed by one or more processors (e.g., processors 502) of one or more computer systems. The computer readable storage medium may include a magnetic or optical disk storage device, solid state storage devices such as flash memory, or other non-volatile memory device or devices. The computer readable instructions stored on the computer readable storage medium may include one or more of: source code, assembly language code, object code, or another instruction format that is interpreted by one or more processors. In various embodiments, some operations in each method may be combined and/or the order of some operations may be changed from the order shown in the figures. For ease of explanation, method 100 is described as being performed by a computer system, although in some embodiments, various operations of method 100 are distributed across separate computer systems.

[0027] While particular embodiments are described above, it will be understood it is not intended to limit the invention to these particular embodiments insofar as they fall within the scope of the invention as set forth in the accompanying claims. Numerous specific details are set forth in order to provide a thorough understanding of the subject matter presented herein. But it will be apparent to one of ordinary skill in the art that the subject matter may be practiced (within the scope of the claims) without these specific details. In other instances, well-known methods, procedures, components, and circuits have not been described in detail so as not to unnecessarily obscure aspects of the embodiments.

[0028] The terminology used in the description of the invention herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the invention. As used in the description of the invention and the appended claims, the singular forms "a," "an," and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will also be understood that the term "and/or" as used herein refers to and encompasses any and all possible combinations of one or more of the associated listed items. It will be further understood that the terms "includes," "including," "comprises," and/or "comprising," when used in this specification, specify the presence of stated features, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, operations, elements, components, and/or groups thereof.

[0029] As used herein, the term "if" may be construed to mean "when" or "upon" or "in response to determining" or "in accordance with a determination" or "in response to detecting," that a stated condition precedent is true, depending on the context. Similarly, the phrase "if it is determined [that a stated condition precedent is true]" or "if [a stated condition precedent is true]" or "when [a stated condition precedent is true]" may be construed to mean "upon determining" or "in response to determining" or "in accordance with a determination" or "upon detecting" or "in response to detecting" that the stated condition precedent is true, depending on the context.

[0030] Although some of the various drawings illustrate a number of logical stages in a particular order, stages that are not order dependent may be reordered and other stages may be combined or broken out. While some reordering or other groupings are specifically mentioned, others will be obvious to those of ordinary skill in the art and so do not present an exhaustive list of alternatives. Moreover, it should be recognized that the stages could be implemented in hardware, firmware, software or any combination thereof.

[0031] The foregoing description, for purpose of explanation, has been described with were chosen and described in order to best explain the principles of the invention and its practical applications, to thereby enable others skilled in the art to best utilize the invention.

Claims

1. A computer-implemented method comprising:

a. receiving, at one or more computer processors, a borehole image, wherein the borehole image traverses a subsurface formation including sand and non-sand layers;
b. dividing (10), via the one or more computer processors, the borehole image into multiple divided borehole images, wherein each divided borehole image traverses a depth interval of the subsurface formation;
c. selecting, via the one or more computer processors, a subset of the multiple divided borehole images for use as training data; **characterized in that** it further comprises the steps of:

d. labeling (12), via the one or more computer processors, the subset of the multiple divided borehole images with sand fraction values based on core analysis such that each depth interval has a corresponding sand fraction value, each sand fraction value being a fraction of the corresponding depth interval that is sand;
e. training (14), via the one or more computer processors, a neural network to predict a sand fraction value using the subset of the multiple divided borehole images labelled with sand fraction values, the training generating a trained neural network; and
f. predicting (17), via the one or more computer processors, a sand fraction value of a further borehole image of a subsurface volume using the trained neural network.

2. The method of claim 1 further comprising augmenting (11) the training data prior to the labeling.

3. The method of claim 2 wherein the augmenting (11) the training data includes azimuthal shifts.

4. The method of claim 2 wherein the augmenting (11) the training data includes depth shifts.

5. The method of claim 1 further comprising using the predicted sand fraction value to estimate (18) at least one of cumulative sand and hydrocarbon in place.

6. One or more computer programs comprising instructions which, when executed by a computer, cause the computer to carry out the method of any of claims 1 to 5.

7. A computer system (500) comprising:

one or more processors (502); and
memory (506),
wherein one or more computer programs are stored in the memory (506) and configured to be executed by the one or more processors (502), the one or more programs including instructions that when executed by the one or more processors (502) cause the computer system to carry out the method of any of claims 1 to 5.

8. A non-transitory computer readable storage medium having the one or more programs of claim 6 stored thereon.

Patentansprüche

1. Computerimplementiertes Verfahren, das Folgendes umfasst:

a. Empfangen, an einem oder mehreren Computerprozessoren, eines Bohrlochbilds, wobei das Bohrlochbild eine unterirdische Formation mit Sand- und Nicht-Sand-Schichten überspannt;
b. Unterteilen (10), über den einen oder die mehreren Computerprozessoren, des Bohrlochbilds in mehrere unterteilte Bohrlochbilder, wobei jedes geteilte Bohrlochbild ein Tiefenintervall der unterirdischen Formation überspannt;
c. Auswählen, über den einen oder die mehreren Computerprozessoren, einer Teilmenge der mehreren unterteilten Bohrlochbilder zur Verwendung als Trainingsdaten; **dadurch gekennzeichnet, dass** es ferner die folgenden Schritte umfasst:

d. Kennzeichnen (12), über den einen oder die mehreren Computerprozessoren, der Teilmenge der mehreren unterteilten Bohrlochbilder mit Sandanteilswerten basierend auf einer Kernanalyse, sodass jedes Tiefenintervall einen entsprechenden Sandanteilswert aufweist, wobei jeder Sandanteilswert ein Sandanteil des entsprechenden Tiefenintervalls ist;
e. Trainieren (14), über den einen oder die mehreren Computerprozessoren, eines neuronalen Netzes zum Vorhersagen eines Sandanteilswerts unter Verwendung der Teilmenge der mehreren unterteilten Bohrlochbilder, die mit Sandanteilswerten gekennzeichnet sind, wobei durch das Trainieren ein trainiertes neuronales Netz erzeugt wird; und
f. Vorhersagen (17), über den einen oder die mehreren Computerprozessoren, eines Sandanteilswerts eines weiteren Bohrlochbildes eines unterirdischen Volumens unter Verwendung des trainierten neuronalen Netzes.

2. Verfahren nach Anspruch 1, ferner umfassend Erweitern (11) der Trainingsdaten vor der Kennzeichnung.

3. Verfahren nach Anspruch 2, wobei das Erweitern (11) der Trainingsdaten Azimut-Verschiebungen beinhaltet.

4. Verfahren nach Anspruch 2, wobei das Erweitern (11) der Trainingsdaten Tiefenverschiebungen beinhaltet.

5. Verfahren nach Anspruch 1, ferner umfassend Verwenden des vorhergesagten Sandanteilswerts zum Schätzen (18) eines kumulativen Sand- und/oder Kohlenwasserstoff-Vorkommens.

6. Ein oder mehrere Computerprogramme, die Anweisungen umfassen, die bei Ausführung durch einen Computer bewirken, dass der Computer das Verfahren nach einem der Ansprüche 1 bis 5 ausführt.

7. Computersystem (500), das Folgendes umfasst:

einen oder mehrere Prozessoren (502); und
einen Speicher (506),
wobei ein oder mehrere Computerprogramme in dem Speicher (506) gespeichert und dazu ausgelegt sind, durch den einen oder die mehreren Prozessoren (502) ausgeführt zu werden, wobei das eine oder die mehreren Programme Anweisungen beinhalten, die bei Ausführung durch den einen oder die mehreren Prozessoren (502) bewirken, dass das Computersystem das Verfahren nach einem der Ansprüche 1 bis 5 ausführt.

8. Nichtflüchtiges computerlesbares Speichermedium, auf dem das eine oder die mehreren Programme nach Anspruch 6 gespeichert sind.

Revendications

1. Procédé mis en oeuvre par ordinateur comprenant :

a. la réception, au niveau d'un ou plusieurs processeurs informatiques, d'une image de puits de forage, l'image de puits de forage traversant une formation souterraine comportant des couches de sable et sans sable ;
b. la division (10), par l'intermédiaire du ou des processeurs informatiques, de l'image de puits de forage en plusieurs images de puits de forage divisées, chaque image de puits de forage divisée traversant un intervalle de profondeur de la formation souterraine ;
c. la sélection, par l'intermédiaire du ou des processeurs informatiques, d'un sous-ensemble des multiples images de puits de forage divisées pour les utiliser en tant que données d'apprentissage ; **caractérisé en ce qu'**il comprend en outre les étapes suivantes :

d. l'étiquetage (12), par l'intermédiaire du ou des processeurs informatiques, du sous-ensemble des multiples images de puits de forage divisées avec des valeurs de fraction de sable sur la base de l'analyse de carottes, de manière à ce que chaque intervalle de profondeur ait une valeur de fraction de sable correspondante, chaque valeur de fraction de sable étant une fraction de l'intervalle de profondeur correspondant qui est constituée de sable ;
e. l'entraînement (14), par l'intermédiaire du ou des processeurs informatiques, d'un réseau neuronal pour prédire une valeur de fraction de sable en utilisant le sous-ensemble des multiples images de puits de forage divisées étiquetées avec des valeurs de fraction de sable, l'entraînement générant un réseau neuronal entraîné ; et
f. la prédiction (17), par l'intermédiaire du ou des processeurs informatiques, d'une valeur de fraction de sable d'une image de puits de forage supplémentaire d'un volume souterrain en utilisant le réseau neuronal entraîné.

2. Procédé selon la revendication 1, comprenant en outre une augmentation (11) des données d'apprentissage avant l'étiquetage.

3. Procédé selon la revendication 2, dans lequel l'augmentation (11) des données d'apprentissage comprend des décalages azimutaux.

4. Procédé selon la revendication 2, dans lequel l'augmentation (11) des données d'apprentissage comprend des décalages en profondeur.

5. Procédé selon la revendication 1, comprenant en outre l'utilisation de la valeur prédite de la fraction de sable pour estimer (18) au moins l'un du sable cumulé et des hydrocarbures sur place.

6. Programme informatique comprenant des instructions qui, lorsqu'elles sont exécutées par un ordinateur, amènent l'ordinateur à mettre en oeuvre le procédé selon la revendication 1 à 5.

7. Système informatique (500), comprenant :

un ou plusieurs processeurs (502) ; et
une mémoire (506),
un ou plusieurs programmes informatiques étant stockés dans la mémoire (506) et configurés pour être exécutés par le ou les processeurs (502), le ou les programmes comprenant des instructions qui, lorsqu'elles sont exécutées par le ou les processeurs (502), amènent le système informatique à mettre en oeuvre le procédé selon l'une quelconque des revendications 1 à 5.

8. Support de stockage non transitoire lisible par ordinateur sur lequel sont stockés le ou les programmes selon la revendication 6.

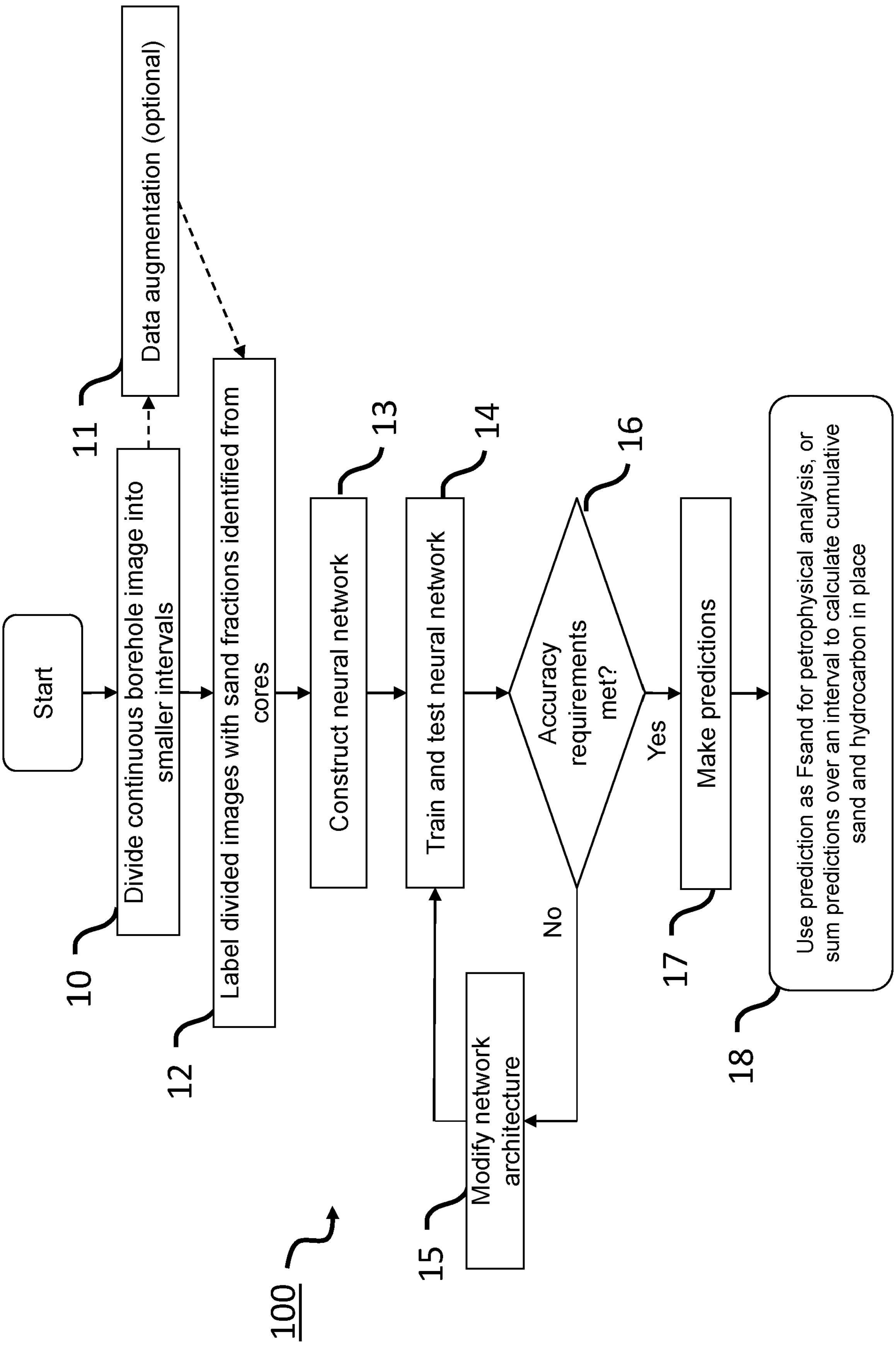
100
Start
10
Divide continuous borehole image into smaller intervals
11
Data augmentation (optional)
12
Label divided images with sand fractions identified from cores
13
Construct neural network
14
Train and test neural network
15
Modify network architecture
16
Accuracy requirements met?
No
Yes
17
Make predictions
18
Use prediction as Fsand for petrophysical analysis, or sum predictions over an interval to calculate cumulative sand and hydrocarbon in place

FIG. 1

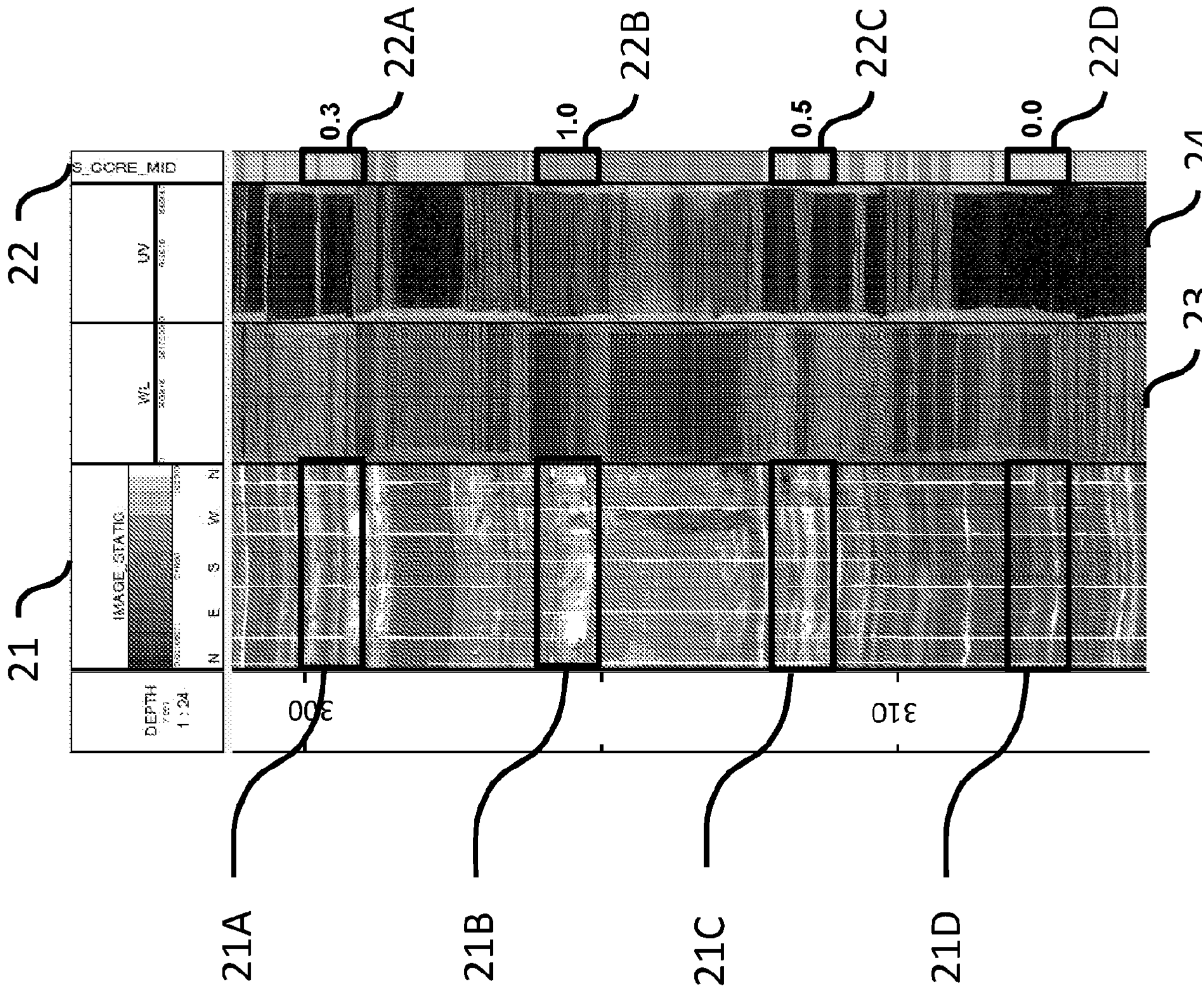
21
22
S_CORE_MID
IMAGE_STATIC
N E S W N
WL
UV
DEPTH
1:24
300
310
0.3
1.0
0.5
0.0
22A
22B
22C
22D
23
24
21A
21B
21C
21D

FIG. 2

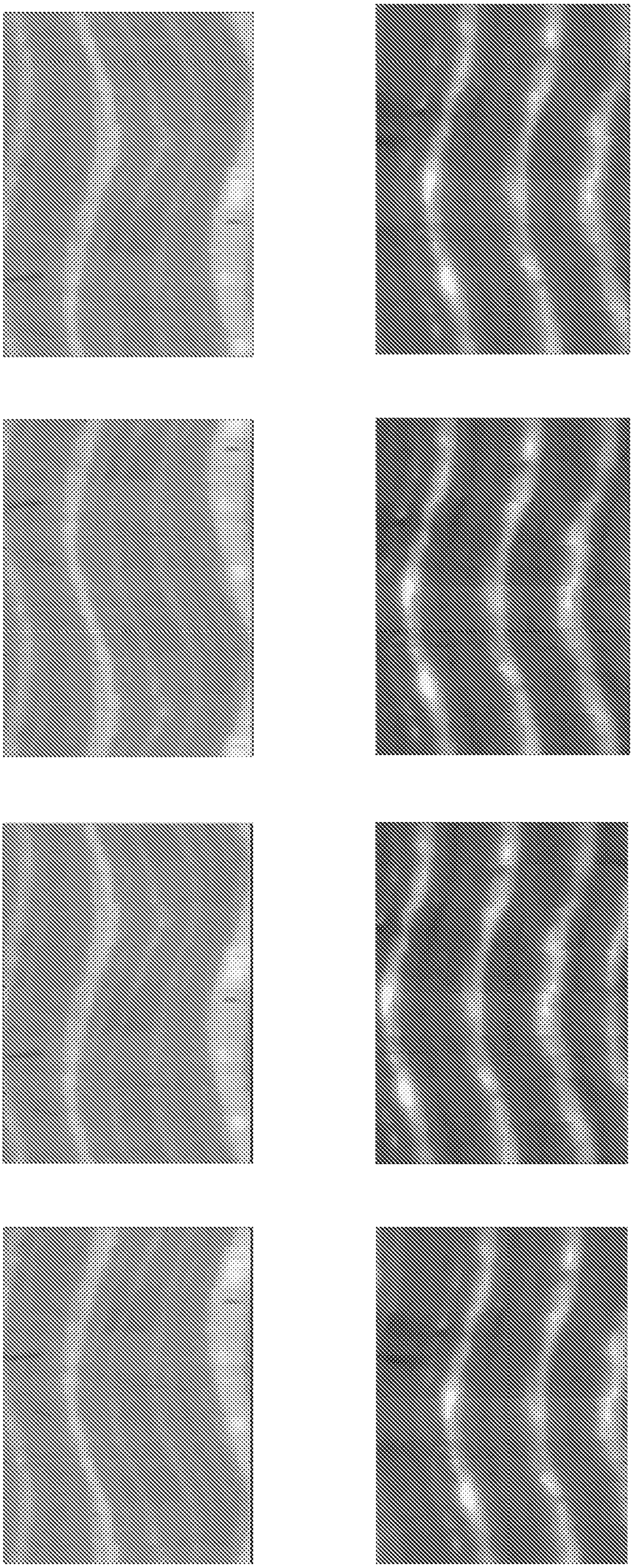

FIG. 3

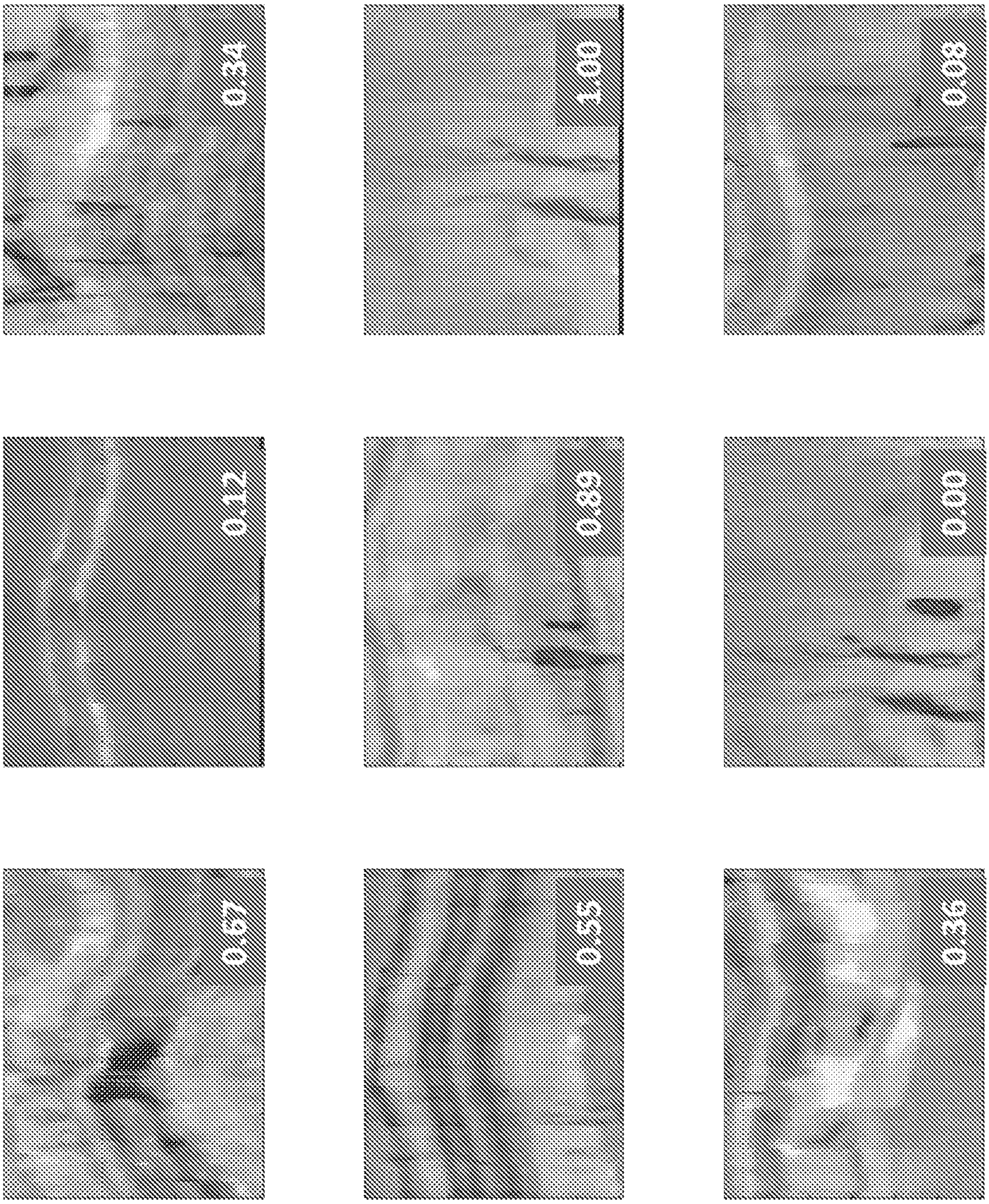

FIG. 4

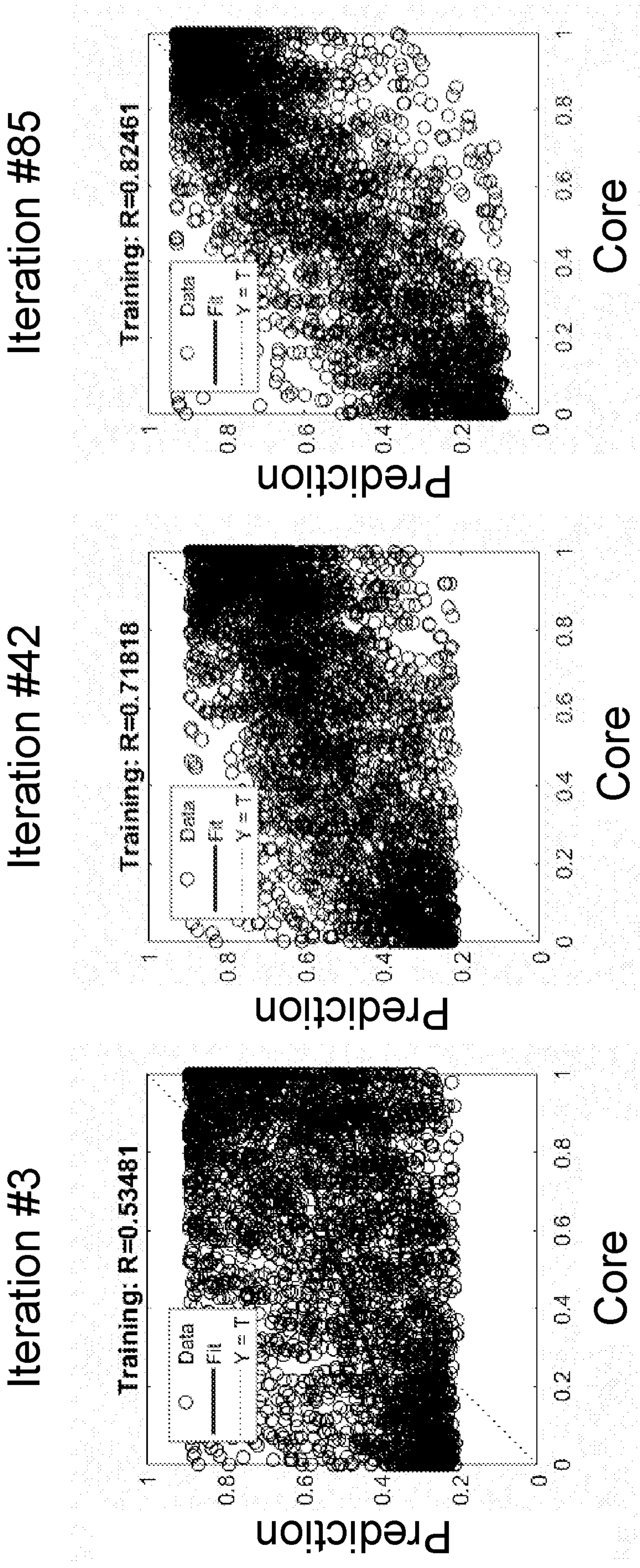
Iteration #3
Training: R=0.53481
Data
Fit
Y = T
Prediction
Core
Iteration #42
Training: R=0.71818
Data
Fit
Y = T
Prediction
Core
Iteration #85
Training: R=0.82461
Data
Fit
Y = T
Prediction
Core
0
0.2
0.4
0.6
0.8
1

FIG. 5

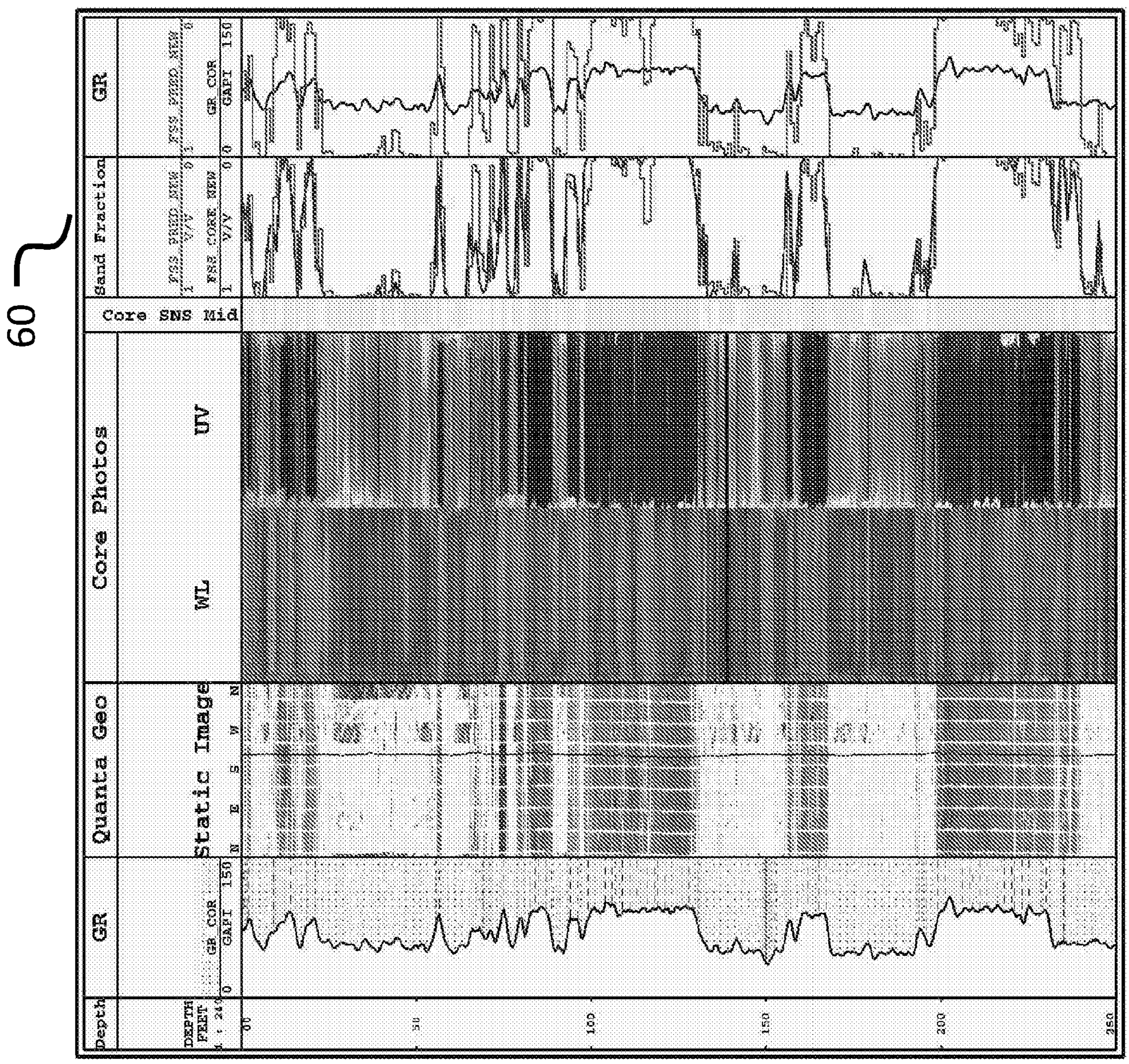
60
Depth
DEPTH
FEET
GR
GR COR
GAPI
0
150
Quanta Geo
Static Image
Core Photos
WL
UV
Core SNS Mid
Sand Fraction
GR
0
50
100
150
200
250

FIG. 6

62

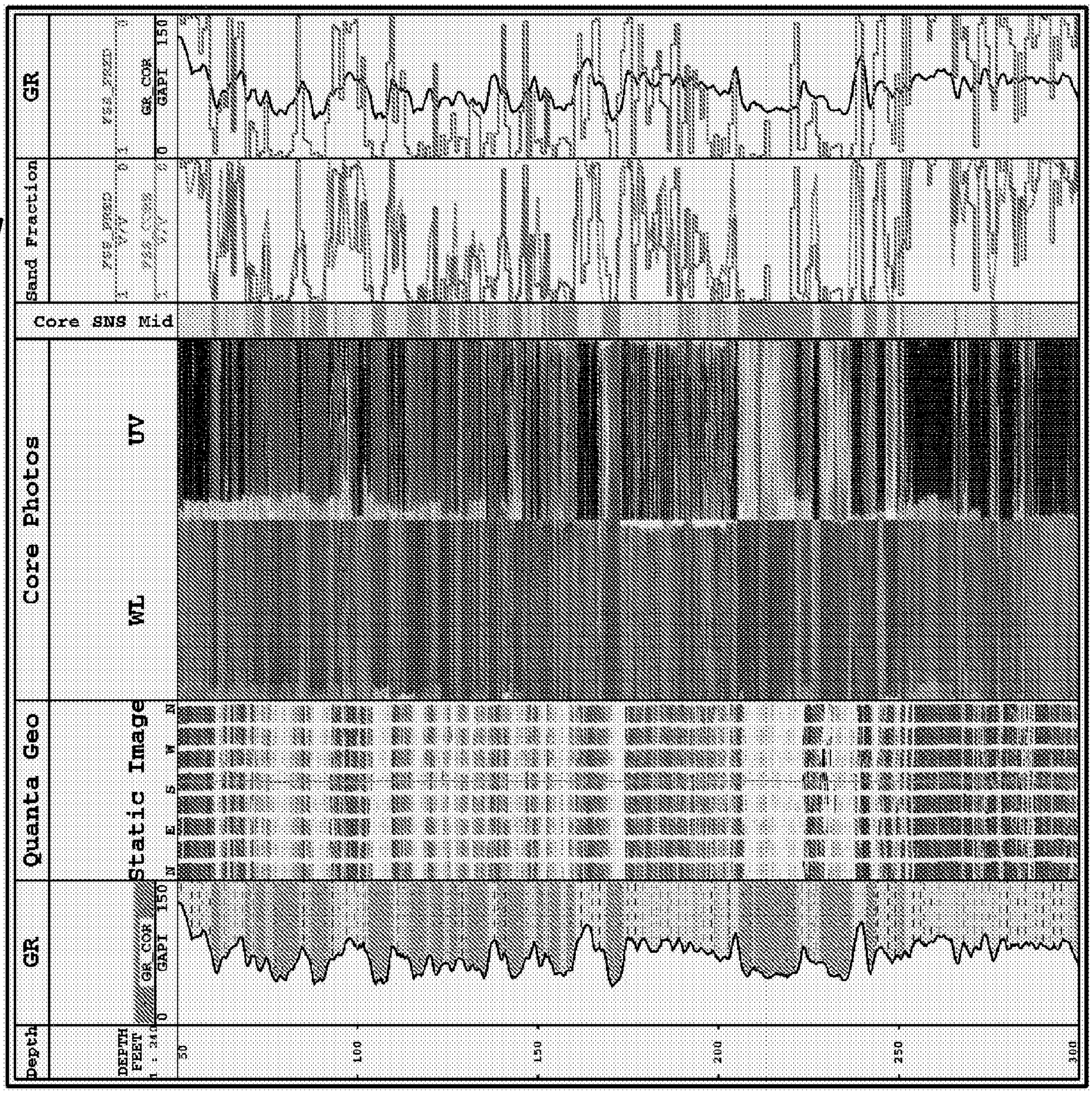
Depth
DEPTH FEET
GR
GR_COR GAPI
Quanta Geo
Static Image
N E S W N
Core Photos
WL
UV
Core SNS Mid
Sand Fraction
GR
GR_COR GAPI
50
100
150
200
250
300

FIG. 7

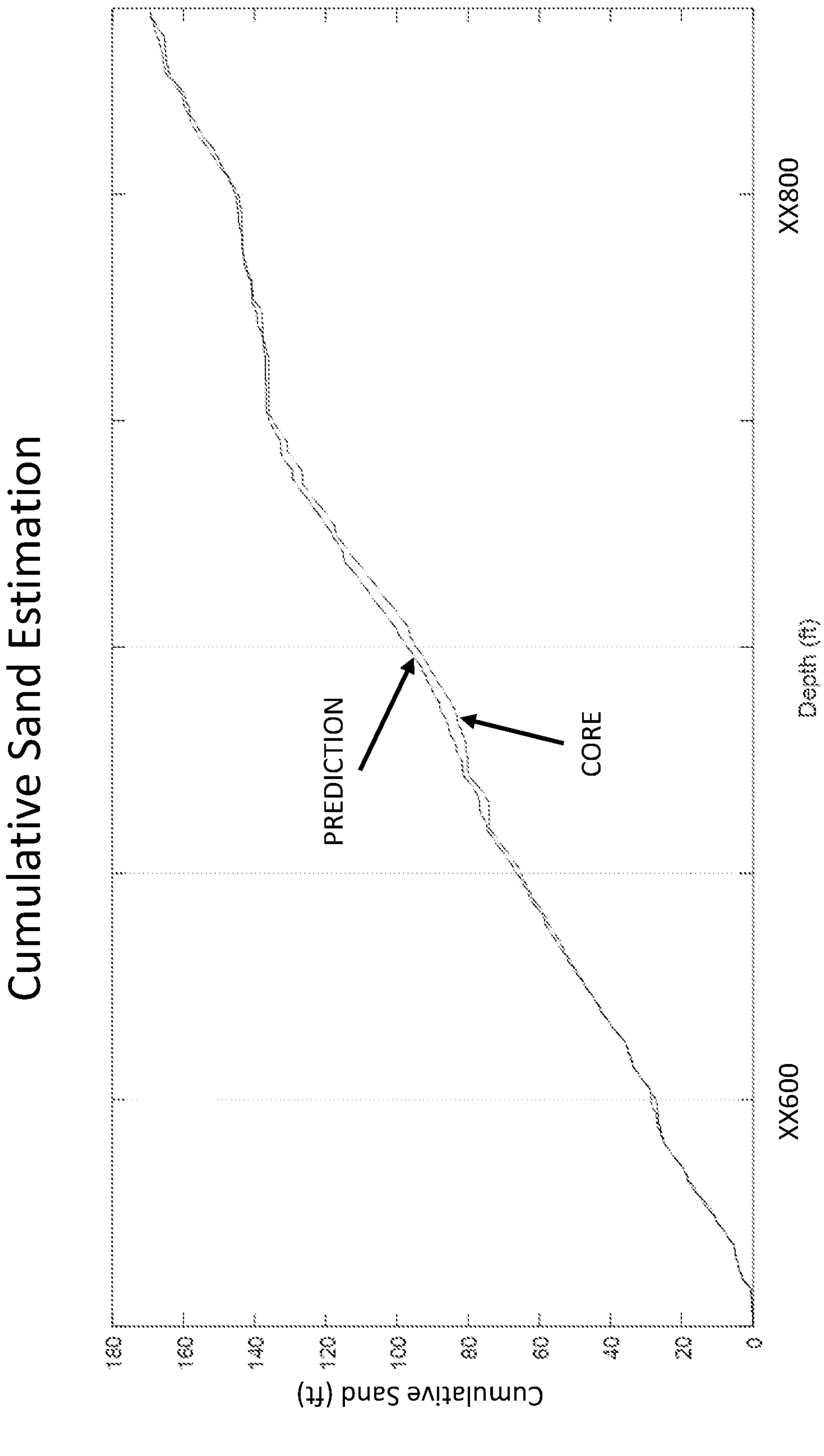
Cumulative Sand Estimation
PREDICTION
CORE
Cumulative Sand (ft)
0
20
40
60
80
100
120
140
160
180
XX600
XX800
Depth (ft)

FIG. 8

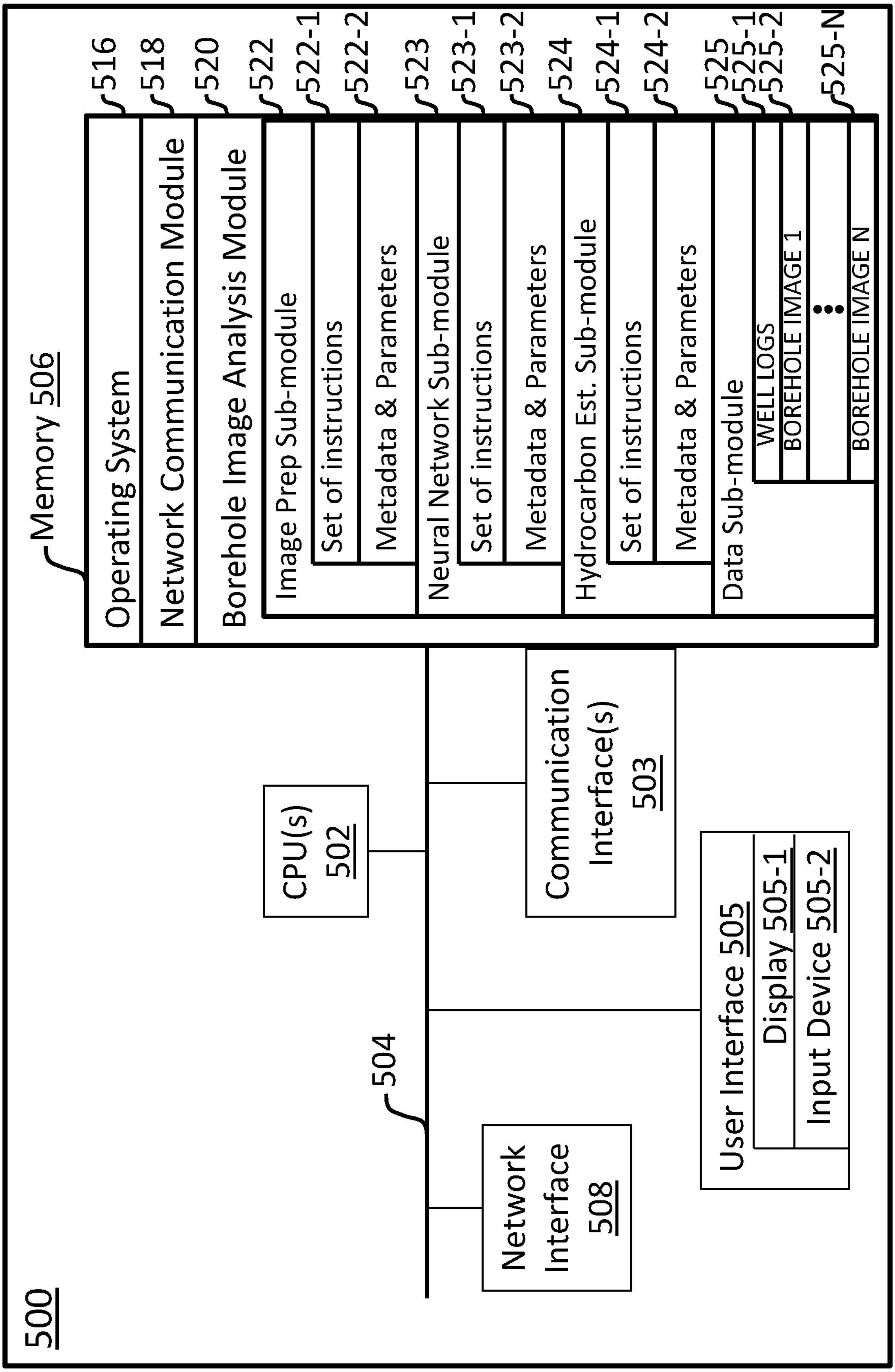
500
Memory 506
Operating System
Network Communication Module
Borehole Image Analysis Module
Image Prep Sub-module
Set of instructions
Metadata & Parameters
Neural Network Sub-module
Set of instructions
Metadata & Parameters
Hydrocarbon Est. Sub-module
Set of instructions
Metadata & Parameters
Data Sub-module
WELL LOGS
BOREHOLE IMAGE 1
BOREHOLE IMAGE N
516
518
520
522
522-1
522-2
523
523-1
523-2
524
524-1
524-2
525
525-1
525-2
525-N
CPU(s) 502
Communication Interface(s) 503
User Interface 505
Display 505-1
Input Device 505-2
Network Interface 508
504

FIG. 9

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- WO 0131365 A1 **[0005]**
- WO 2015127349 A1 **[0005]**
- WO 2014070572 A2 **[0005]**